

**DEVELOPMENT OF A DISCRETE WAVELET
TRANSFORM AND ARTIFICIAL NEURAL
NETWORK BASED CLASSIFICATION SYSTEM
FOR MAMMOGRAM IMAGES**

by

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In the Name of Allah, the most Beneficent, the most Merciful
{ Allah will raise those who have believed among you and those who were given
knowledge, by degree. And Allah is acquainted with what you do }

Surah Al-Mujaadila (11)

DEDICATION

To my supervisor Professor Dr. Nor Ashidi Mat Isa

To my parents, who have made me, the man I am today

To my dearest friends Dr. Khamees Khalaf and Ph.D. student Mr. Salam Mohammed

To my dear wife Trifa for her unlimited love, support, patience and encouragement;

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LIST OF ABBREVIATIONS

Abbreviation	Description
1-D	One Dimension
1D-DWT	One Dimension Discreet Wavelet Transform
2-D	Two Dimensions
2D-DWT	Two Dimension Discreet Wavelet Transform
3-D	Three Dimension
A	Approximation Subband
AMBE	Absolute Mean Brightness Error
AAMBE	Average Absolute Mean Brightness Error
ABC	Artificial Bee Colony
AMLT	Adaptive Multilevel Threshold
ANN	Artificial Neural Network
ANCE	Adaptive Neighborhood Contrast Enhancement
AMBE	Absolute Mean Brightness Error
AUC	Area Under the Curve
BP	Backpropagation
BPANN	Backpropagation Artificial Neural Network
BPN	Backpropagation Network
CAD	Computer Aided Diagnosis
CBT	Clustering-based Thresholding
CLAHE	Contrast Limited Adaptive Histogram Equalization
CT	Computed Tomography
D	Diagonal subband

dB	Decibel
DCIS	Ductal Carcinoma In Situ
DDSM	Digital Database for Screening Mammography
DWT	Discrete Wavelet Transform
ECGs	Electrocardiography
EEGs	Electroencephalogram
ELMANN	Extreme Learning Machine Artificial Neural Network
EM	Expectation Maximization
FFDM	Full Field Digital Mammogram
FN	False Negative
FNF	False Negative Fraction
FANC	Fine Needle Aspiration Cytology
FP	False Positive
FROC	Free Response Operating Characteristic
GA	Genetic Algorithm
GLCM	Gray Level Co-occurrence matrix
GLRLM	Gray Level Run-Length Method
GMRF	Gaussian Markov Random Field
GN	Genetic Network
H	Horizontal subband
HE	Histogram Equalization
HH	High-High
HL	High-Low
HMLP	Hybrid Multilayer Perceptron
HT	Histogram Shaped-based Thresholding

HWT	Haar Wavelet Transform
IARC	International Agency for Research Center
IT	Information-based Thresholding
KNN	K-Nearest Neighborhood
LDA	Linear Discriminate Analysis
LH	Low-High
LL	Low-Low
LM	Levenberg Marquard
LMLO	Left Medio-Lateral Oblique
LMS	Least Mean Square
LT	Locally Adaptive Thresholding
MC	Microcalcification
MIAS	Mammographic Images Analysis Society
MLP	Multilayer Perceptron
Mod-max	Modules-maximum
MPM	Maximizer of the Posterior
MPV	Mean Pixel Value
MRA	Multi-Resolution Analysis
MRF	Markov Random Field
MRI	Magnetic Resonance Imaging
MSE	Mean Squared Error
MWA	Multiresolution Wavelet Analysis
OAT	Object Attribute Thresholding
PCA	Principal Component Analysis
PET	Positron Emission Tomography

PNN	Probabilistic Neural Network
POSWNN	Particle Swarm Optimization Wavelet Neural Network
PSNR	Peak Signal to Noise Ratio
PSO	Particle Swarm Optimization
RBF	Radial Basis Function
RMLO	Right Medio-Lateral Oblique
ROC	Receiver Operating Curve
ROI	Region of Interest
SFM	Screen Film Mammogram
SGLDM	Spatial Gray Level Dependency Matrix
SONN	Swarm Optimization Neural Network
SVM	Support Vector Machine
TN	True Negative
TP	True Positive
TPF	True Positive Fraction
TWSVM	Twin Support Vector Machine
UK	United Kingdom
US	Ultrasonography
V	Vertical subband
WHO	World Health Organization

LIST OF SYMBOLS

Symbol	Description
d	Difference between mean and median
f_r	Reduction Factor
R_{inner}	Inner Binary Mask
R_{outer}	Outer Binary Mask
$R_{skin-air}$	Skin-air Interface Region
$R'_{skin-air}$	Binary Breast Profile LMLO
$R''_{skin-air}$	Binary Breast Profile RMLO
T_0	Initial Threshold
T_n	Current Threshold
T_{inner}	Inner Threshold
T_{outer}	Outer Threshold
μ	Mean Value
δ	Median Value
$\Phi(x)$	Haar Scaling Function
$\Psi(y)$	Haar Wavelet Function
$\Phi(x,y)$	Approximation Subband
$\Psi(x,y)$	Detail Subband

**PEMBANGUNAN SISTEM PENGKELASAN BERASASKAN JELMAAN
GELOMBANG KECIL DISKRET DAN RANGKAIAN NEURAL BUATAN
UNTUK IMEJ MAMOGRAM**

ABSTRAK

Pada masa ini, terdapat pelbagai sistem diagnosis bantuan komputer (CAD) yang dibangunkan sejak beberapa tahun lalu untuk membantu ahli radiologi dalam pengecaman lesi mamografi yang boleh menunjukkan kehadiran kanser payudara. Walau bagaimanapun, prestasi CAD terhad oleh dua isu utama iaitu (i) kawasan yang tidak diingini (seperti label segi empat tepat berintensiti tinggi, pita, artifak, antara muka kulit dan air, dan lain-lain) yang boleh mengganggu pengecaman kanser payudara dan mengurangkan kadar ketepatan CAD, (ii) ketidakteraturan tekstur mamogram yang meliputi ciri-ciri seperti entropi, tenaga, kepencongan, kurtosis, min dan sisihan piawai yang berhubung kait dalam domain ruang dan tidak penting untuk pengelasan. Oleh itu, bagi menangani masalah yang dinyatakan di atas, sistem CAD yang lebih baik untuk imej mamogram dicadangkan. CAD yang dicadangkan ini terdiri daripada tiga peringkat utama, iaitu prapemprosesan, pengekstrakan ciri dan pengelasan imej mamogram. Pada peringkat prapemprosesan, *Adaptive Multilevel Threshold* (AMLT), yang berjaya menyingkirkan kawasan yang tidak diingini seperti yang dinyatakan sebelum ini, dicadangkan. Hal ini memberikan kelebihan kepada sistem dengan membolehkan pencarian terhadap keabnormalan terkekang pada lingkungan tisu payudara tanpa menjejaskan kawasan yang tidak diingini dalam latar belakang imej. Pada peringkat pengekstrakan ciri, dua ciri baharu iaitu median maksimum dan minimum subjalur berfrekuensi tinggi dicadangkan untuk pengelasan imej mamogram kepada kategori normal, benigna dan malignan. Analisis plot kotak membuktikan bahawa kedua-dua ciri baharu tiada hubung kait dan penting untuk

pengelasan imej mamogram berbanding dengan ciri-ciri konvensional. Pada peringkat pengelasan, rangkaian perseptron berbilang lapis (MLP) digunakan untuk mengelaskan mamogram normal dan tidak normal pada fasa pertama dan mamogram benigna dan malignan pada fasa kedua. Keputusan purata yang terhasil daripada 322 imej mamogram pada fasa pertama merumuskan bahawa pendekatan yang dicadangkan berjaya mencapai keputusan yang boleh harap dengan ketepatan sebanyak 96,27%, kepekaan sebanyak 94,78% dan kekhususan sebanyak 96.60%. Di samping itu, keputusan purata yang terhasil daripada 115 imej yang tidak normal mempunyai ketepatan, kepekaan dan kekhususan, masing-masing sebanyak 95.65%, 96.18% dan 95.38%. Keputusan eksperimen akhir menunjukkan bahawa sistem pengelasan mamogram yang dibangunkan mampu mencapai pengelasan tertinggi berbanding dengan sistem terkini yang lain. Prestasi pengelasan yang menggalakkan ini menunjukkan bahawa sistem yang dicadangkan tersebut boleh digunakan untuk membantu ahli patologi dalam menjalankan proses diagnosis.